# REVIEW OF ARTIFICIAL INTELLIGENCE AND HUMAN THINKING

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## ABSTRACT

Many fields, including formal logic, probability theory, decision theory, management science, linguistics, and philosophy, have contributed to the development of tools and approaches of AI research. The implementation of these disciplines in AI, on the other hand, has marked the beginning of several innovations and extensions. Computational logic approaches are among the most powerful of these. Computational logic integrated in an agent cycle, according to the study, incorporates and enhances both conventional logic and classical decision theory. Many of these approaches in the study may be applied not just in AI, but also in everyday life to help individuals improve their own intelligence without the help of computers, according to the authors.

**Keywords:** Artificial Intelligence, Human intelligence**.**

## INTRODUCTION

Computational logic, like other types of logic, comes in a variety of shapes and sizes. The abductive logic programming (ALP) kind of computational logic will be the subject ofthis study.

The ALP agent model is a dual process theory that blends intuitive and deliberative thinking for its descriptive and normative characteristics. Dual process theories, like most theories, exist in a variety of shapes and sizes.However, intuitive thinking “quickly suggests intuitive responses to judgment questions and concerns,” as [4] put it, but deliberative thinking “observes the reliability of these recommendations, some of which may approve, correct, or override.”

### A. A Brief Introduction to ALP Agents

The ALP agent model is a variation of the BDI model, in which agents utilize their beliefs to generate intentions, which are pre-determined plans of action, to meet their desires. In the clausal type of logic, beliefs and wants (or objectives) are both expressed as conditionals in ALP agents. With the expressive capacity of full first-order logic, beliefs are expressed as logic programming clauses, while objectives are expressed as more generic sentences (FOL). The first line below, for example, indicates a purpose, whereas the other four words express beliefs:

If there is a crisis, I deal with it alone, seek assistance, or flee. If there is a fire, it is an emergency. If I'm aboard a train, I seek assistance and notify the train's driver. If I'm aboard a train, I call out to the conductor and push the alarm button. I'm aboard a train right now.

Goals are given conditions first in this article, since they, like regular expressions, are always utilized to reason ahead. Because, like logic programmes, beliefs are frequently included to reason backwards, they are generally written with the conclusion first. However, beliefs are quite often written first since they may be used to reason backwards and forth in ALP. It makes no difference whether conditionals are expressed forwards or backwards in terms of semantics.

### i. Model-theoretic and Operational Semantics

In the semantics of ALP agents, beliefs represent the world as the agent perceives it, whereas goals reflect the world as the agent wishes it to be. Beliefs handle information in deductive databases, whereas objectives constitute data structures and integrity restrictions.

The objective of an agent with beliefs B, goals G, and predictions O in the model-theoretic semantics of the ALP agent model is always to produce a sequence of behaviors and hypotheses about the environment such that: G O is true in the minimum model given by B. B always seems to have a distinctive minimum model in the basic situation when B is a set of Horn clauses.Other situations can be simplified towards the Horn clause case, however the details are unimportant in this case. ALP agents use operational semantics to reason forwards from observations and backwards from beliefs to determine if an instance of a goal's precondition is true, and to deduce the matching occurrence of the goal's conclusion as an accomplishment goal, to become accurate. Forward reasoning through observations is similar to forward chaining in production systems in that it aims to make the objective true by rendering the inference true however when the criteria are met. Conditional objectives are sometimes known as maintenance goals when seen in this light.

Goals are solved by working backwards, looking for a plan of action that will accomplish the objectives. Executable actions are a specific case of atomic sub-goals, and backwards reasoning is a type of goal- reduction.

Consider the following scenario: I notice a fire. I may then reason using the above-mentioned aim and beliefs, establishing that there is an urgency and drawing the accomplishment goal of dealing with it alone, getting help, or fleeing. These three options provide a starting point for your search.

By thinking backwards and limiting the objective, I can solve the accomplishment goal. I obtain assistance with the subsequent sub-goals. I call out to the train's conductor and push the emergency alarm. Even though the last sub-goal is an atomic action, it can be carried out immediately. If the activity is successful, it fulfils both the accomplishment and this occurrence of the maintenance goals.

The agent must produce not just actions, but also perceptions of the world in model-theoretic semantics. The term "abduction" is used in ALP because of these notions. The fabrication of hypotheses to explain observations O is known as abduction. For example, instead of seeing fire, I may notice smoke and conclude that there is smoke if there is a fire. The presumption that there is a fire is then generated by

reasoning backwards from the observation. The previous steps of forward and backward reasoning are then repeated.

Observations O and goals G are addressed similarly in model-theoretic and operational semantics, through reasoning forwards and backwards to produce behaviors and other implications, in order to make G O true in the minimum model of the world given by B. Given O = there's really smoke, then = there is indeed a fire, I push the emergency stop button coupled with B, which renders both G and O true.

In terms of model-theoretic semantics, the functional semantics is sound. It's also complete under reasonable assumptions.

### ii. Choosing the Best Solution

There might be multiple choices that, when combined with B, prove G and O true. They can have a variety of values, and an intelligent agent's job is to discover the optimal solution feasible given the cognitive resources that are available.

The expected utility of an action's effects is used to determine its worth in classical causal inference. The worth of an explanation is assessed on the basis of its probability and explanatory power in scientific philosophy. (The more details you provide, the better.) The very same measures may be used to assess candidate actions and candidate explanations in ALP agents.In both cases, candidate assumptions in are evaluated by reasoning forwards to generate consequences of the assumptions in.

The task of identifying the best is integrated into the search method for reasoning backwards to produce in ALP agents, which uses some kind of best-first search, such as A* or branch-and-bound. This issue is similar to the considerably easier challenge of resolving disagreement in production systems.

Compiling higher-level objectives, beliefs, and judgments into lower-level heuristics and stimulus- response connections is how traditional production systems avoid sophisticated decision-theory and abductive reasoning. Consider the following scenario:
Unless there is smoke while I am on a train, I will not use the alarm.

Lower-level rules and higher-level reasoning and decision-making can be mixed in ALP agents to achieve the perfect combination, as in dual process theories.

ALP agents, like BDI agents, mix reasoning with perceiving and responding, and they don't need to make detailed preparations before acting. Unlike other BDI agents, who choose and adhere to a single plan at a moment, ALP agents choose and commit to specific actions alone.

Unlike many other BDI agents, ALP agents might pursue many alternative strategies at the same time to increase their chances of success. During an emergency, for example, an agent can hit the alarm button while also attempting to flee at the same time. The search strategy determines whether an ALP agent operates on one program or numerous alternatives at the same time. While depth-first search focuses on one approach at a time, alternative search methods are frequently preferred.

The ALP agent model may be used to create artificial agents, and it could also be used to describe human thought and decision-making. However, I will show in the rest of this paper that it may also be utilised as a normative (or prescriptive) model that incorporates and enhances both conventional logic and classical decision theory.

The justification for using the ALP agent model to design a stronger decision theory is based on the premise that ALP's clausal logic provides a realistic description of thinking language (LOT). In the following sections, I shall compare clausal logic to natural language to prove this assertion.

### iii. Clausal Logic as an Agent's LOT

There are three major schools of thought in the philosophy of language discussing the interrelationship between language and mind:

- The LOT is a private, language-like representation that is distinct from public, natural languages.
- The LOT is a type of public language, and the natural language we use impacts how we think.
- Human thought lacks a linguistic framework.

The ALP agent model is a member of the first school of thinking, which contradicts the second but is consistent with the third. It challenges the second school, primarily since this ALP logical model of thinking doesn't really need the presence of natural languages, and also since human language is too imprecise and inconsistent, according to AI standards, to operate as a viable model of human thought.

The idea how an agent's LOT is some sort of logic is closely linked with GOFAI (plain old fashioned AI), which has now been partially eclipsed in past few years by connectionist and Bayesian methods. I'll propose that the ALP model of thinking has the ability to bridge the gap across logic, connectivism, and Bayesian methods. That's because ALP's clausal logic is considerably easier than normal FOL, does have a connectionist implementation that supports Bayesian certainty, and is related to ordinary FOL in the same way as the LOT is related to natural language.

The argument's first strategy mainly focuses on relevance theory [6], which states that humans comprehend natural language by striving to retrieve as much data as possible for the least amount of processing time. As a derivative of the idea, the closer a communication is to its actual intent, the simpler it is for a reader (or listener) to discern the message's meaning.

Thus, one method to assess if there is a LOT and what it may appear like to consider instances where understanding a message as desired and with very little exertion as feasible is a matter of survival. We shall see how the communication becomes easy to grasp in the instance of the London Underground Emergency Notice since the English phrases are organized expressly or by implication as logical conditionals.

## iv. A Connectionist Form of Clausal Logic

The connection graph proof process employs clausal logic by precompiling linkages between prerequisites and inferences and labelling links with their unifying replacements, analogous to how clausal logic implements FOL by first transforming sentences into binary format. These linkages can then be triggered at a later time, either forward or backwards, as needed. In the same way as heuristic rules and stimulus-response connections may be collected into shortcut keys, that may accomplish the same results more effectively, links which are triggered frequently can be combined into shortcuts.

Since clausal logic is a literal description, the identities of the predicate symbols are irrelevant after all the connections and their integrating replacements have been calculated. All subsequent reasoning may be simplified to the triggering of links and the production of new premises with new connections acquired from respective parent clauses' linkages. When all of their linkages have also been triggered, parent clauses can often be removed or modified. At a certain moment, any connection can be chosen for execution. However, only some of the time, activating linkages makes complete sense just when new clauses are introduced to the network as a consequence of recent findings, particularly communications observations. Assigning various strengths to distinct findings and goals, indicating their respective relevance, can help to guide the reactivation of connections (or utility). Furthermore, multiple parameters can be applied to distinct connections, indicating statistical data on when and where their activation has previously contributed to good results.

In proportion to the weights on the links, the intensity of findings and objectives may be transmitted across the graph. The proof method that results, that triggers linkages with currently highest weighted strength, is comparable to [7] activation networks. Furthermore, it employs an ALP-style of forward and backward reasoning, as well as a type of best-first search.

The connection graph model of thinking might provide the false impression that thinking is completely devoid of linguistic or logical components. However, the contrast between thought process in link graphs and reasoning in clausal logic is the same as the differences between an optimized, low-level implementation that is similar to the hardware and a high-level representation that is close to the given problem in traditional computer science.

The mind's connection network model lends credence to the idea that thinking actually occurs in a LOT that is separate from regular language. The LOT may aid in the formation of natural language, but it is not necessary for it to exist.

According to the connection graph concept, articulating thoughts in plain language is similar to simply changing low-level programmes into higher-level programme specifications. Decompiling programmes is difficult in computing. This may assist to understand why putting our ideas into words is so difficult.

### v. Representing Uncertainty

Internal linkages, which structure the agent's ideas, and exterior links, which root the agent's thoughts in reality, are both included in connection graphs. Observations and the agent's own activities trigger the external linkages. They might potentially contain references to world features that aren't visible. The agent can assume things about all of these features and try to assess their likelihood. The likelihood that a hypothesis is correct influences the likelihood that an agent's actions will result in a certain result. Consider the following scenario:
If you buy a lottery ticket and your number is drawn, you will be wealthy. If you do a rain dance and the gods are pleased, it will rain.

You have influence over your own activities (such as purchasing a ticket or doing a rain dance), however you may not always have influence on the actions of others or the status of the world (your number is chosen or the gods are pleased). At most, you may be responsible for assessing the likelihood that now the world is or will be in a specific state (one in a million?). Associating probabilities with such assumptions provides ALP the expressive capacity of Bayesian networks, according to [3]

## I. OBJECTIVE OF THE STUDY

The paper's primary purpose is to investigate Artificial Intelligence and Human Thinking.

## II. LITERATURE REVIEW

This article gives an overview of the most common deep learning techniques and research areas suggested during the last ten years. It's crucial to note that, based on the location and environment in which it's utilized, each technique has strengths and "weaknesses." As a result, this article provides a review of the current status of the deep machine learning discipline as well as some insight into where it may develop in the future. The priority is on Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) (and their variants) since they are well-established in the deep learning area and offer tremendous potential for future research. [1]

Many contemporary real-world financial applications feature nonlinear and unpredictable characteristics that vary over time. As a result, the need for solutions to highly nonlinear, time-variant issues is quickly increasing. These issues, as well as other issues with traditional models, sparked a surge in interest in artificial intelligence approaches. In this study, a comparative case study review of three well-known artificial intelligence approaches in the financial sector has been conducted, namely, artificial neural networks, expert systems, and hybrid intelligence systems. Credit appraisal, portfolio management, and financial forecast and planning are the three areas of a financial market. For each approach, the most well-known and, in particular, recent studies have been compared. The reliability of these artificial intelligence techniques in dealing with financial difficulties is comparable to that of traditional statistical

methods, particularly when combined with nonlinear patterns, according to the findings. This overvaluation, though, is not comprehensive. [2]

## III. CONCLUSION

The study proposes two methods wherein the ALP agent model, which is based on a number of AI advancements, may be utilized by ordinary people to increase their own human intelligence. [5] It can assist individuals in expressing their views more clearly and logically, as well as making better decisions. The use of such approaches is a viable area for collaboration between AI researchers and researchers in more humanistic fields in the future.

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